Lung Nodule Classification Using Deep Features in CT Images

Devinder Kumar, Alexander Wong, and David A. Clausi

UNIVERSITY OF WATERLOO
FACULTY OF ENGINEERING
Department of Systems Design Engineering

June 5th, 2015

Outline

- Why?
  - Motivation
- What?
  - Proposed Approach
- How?
  - Exp. Setup
- So, What?
  - Future Work

Challenges and Motivation

- Why?
  - Lung cancer results in **17%** of total cancer related deaths.
  - **Early diagnosis** required as it is harder to contain in later stages.
  - **Burden** on doctors for early diagnosis.
  - **Untapped data** is now available to build effective computer aided diagnosis (CAD) systems.
- <u>Goal</u>: **second opinion**!

- Build an effective CAD system to classify annotated nodules as malignant or benign using *deep* features extracted from autoencoder and binary decision tree as classifier.

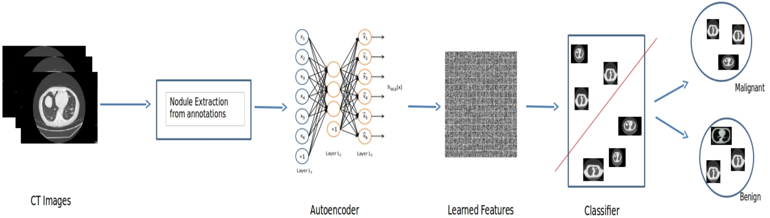
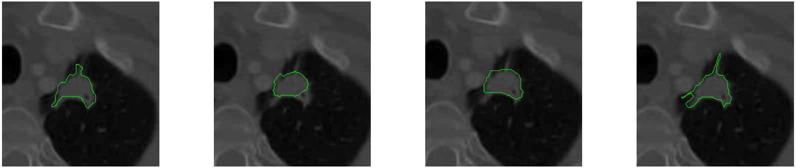


Figure : Proposed system flow diagram

CAD system Design : Dataset

- LIDC-IDRI dataset
  - Thoracic CT images of 1010 patients
  - Diagnostic data for 157 patients avialable (ground truth)
    - Ratings: 0-Unknown, 1-benign, 2-Primary malignant, 3-metastatic
  - Annotations provided!
  - Nodule size: 3 mm to 30 mm

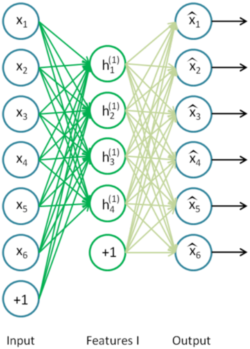


(A) (C) (B) (D)

Figure : Annotations provided by four different radiologists

CAD system Design : Autoencoder

- Design:
  - Encoder
  - Decoder



Autoencoder

- Let
  - input be $f(x^i)\epsilon\ [0,1]^d$
  - latent space $y\epsilon[0,1]^d$
  - ϕ be non linear function

$$y = \phi(Wf(x^i) + b) \tag{1}$$

- Reconstruction:

$$f(x^i)' = \phi(W'y + b') \tag{2}$$

- Error minimization:

$$\min_{W,b} \sum_{i=1}^{n} \parallel f(x^i)' - f(x^i) \parallel^2 \tag{3}$$

Stacked Autoencoder

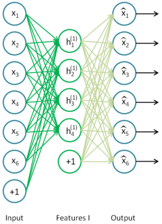


Figure : Stacked autoencoder formation

Stacked Autoencoder

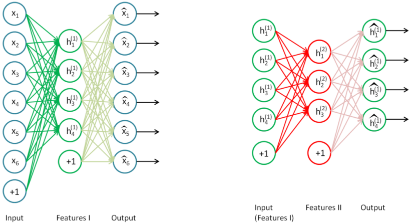


Figure : Stacked autoencoder formation

Stacked Autoencoder

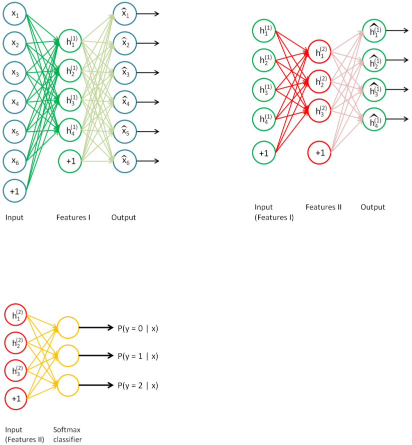


Figure : Stacked autoencoder formation

Stacked Autoencoder

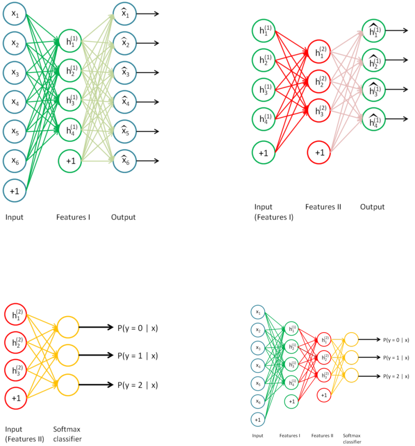
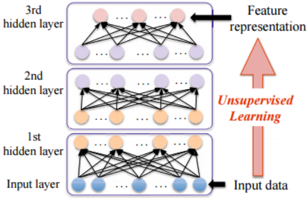


Figure : Stacked autoencoder formation

Stacked Autoencoder

- Our Design
  - 3 Hidden layers
  - layer size 200,100,200
  - Iteration set: 30
  - Batch size: 400
  - Feature extraction at 3rd hidden layer



Experimental Setup

- Data: 4303 Instances (4323 nodules)
  - Obtained from diagnostic data
  - all provided annotation considered
  - Rating: 1: benign & 0,2,3: malignant
- Feature extraction: features are extracted from 4th layer (3rd hidden layer)
  - 200 dim. vector
- Training:
  - 90% of 4303 Instances
  - 10-fold cross validation

Results

- 10 fold cross validation avg. :
  - Accuracy: 75.01
  - Sensitivity: 83.35
  - FP/patient: 0.39

	Deep Features	Belief Decision Trees[1]
Accuracy	**75.01%**	68.66%

[1] D. Zinovev et al., Probabilistic lung nodule classification with belief decision trees in EMBC, 2011 Annual International Conference of the IEEE. IEEE, 2011, pp. 44934498

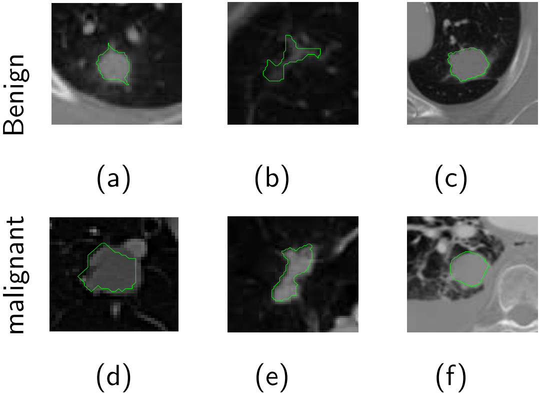


Figure : significant visual similarities between the annotated nodules in (a,d), (b,e) and (c,f), making it very difficult to differentiate between such nodules during the classification process.

- So,What?

Future Work

- different deep architectures (e.g. CNN) & more hidden layers i.e. *very deep* networks (16-19 layers)
- combination of features
- STAPLE
- SPIE lung nodule classification challenge
- Automatic nodule detection

Thank you for listening!

Contact: Devinder Kumar
Email: devinder.kumar@uwaterloo.ca